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Multi-objective planning of distributed energy resources: A review of the state-of-the-art

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ABSTRACT

The use of Distributed Energy Resources (DER) has been proposed as one of the possible solutions to today's energy and environmental challenges. The optimal integration of DER in distribution networks is essential to guarantee the best of resource, i.e. maximize their benefits, such as reduction of carbon emissions, reduction of network energy losses and to minimize the negative impacts, which can affect the network quality, cause network sterilization and increase investment and operation costs. Hence, DER planning is a multi-objective problem in which many objectives of interest, sometimes conflicting, need to be optimized simultaneously, and where a compromise for different perspectives (DER developer, Distribution System Operator, regulator) needs to be found. Appropriate multi-objective planning methods that consider technical, environmental and economic impacts of DER integration, and that are able to support a suitable model of stochastic DER and active networks, can provide a deep insight into the case specific and general advantages and drawbacks of DER. Consequently, the interest in multi-objective DER planning has increased in recent years, and a number of novel methods have been proposed in this area. This paper provides a timely review of the state-of-the-art in multi-objective DER planning, and discusses in detail the challenges, trends and latest developments in this field.

Contents

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1. Introduction

1.1. Background

In recent years, climate change has prompted international awareness about the impacts that electricity generation and the use of energy have on the environment. In this context, local generation of heat and electricity and the local use of renewable energy resources are considered as some of the most promising options to provide a more secure, clean and more efficient energy supply [1].

Distributed Generation (DG) is defined as "an electric power source connected directly to the distribution network or on the customer site of the meter" [2]. The most common DG technologies include Combined Heat and Power (CHP) generators, micro-turbine gas generators, solar photovoltaic generators (PV), wind generators and micro-hydro schemes [3]. At present, DG is considered within the broader concept of Distributed Energy Resources (DER), which also includes responsive loads and energy storage [4].

1.2. The need for optimal DER integration

Several benefits can be obtained when DER is correctly integrated. For example, DER located close to load centers and with a production coincident with demand reduces power flow in lines. This reduction in power flows results in an improvement of voltage profile, and in a decrease in the line losses [3]. Moreover, if DER produces power at peak times, network investments can be deferred [5]. Similarly, the reliability of the network can be increased by DER with constant production and connected to meshed grids, or by DER that are allowed to operate in islanded mode while connected to radial networks. In contrast, DER with a variable output, such as wind generators, or DER connected to radial networks and not allowed to work in islanded mode do not increase the reliability of the network [3].

Many of these technical effects translate to economic benefits for the Distribution System Operator (DSO) (e.g. reduction of line losses, investment deferral, increased reliability), or for the customer (e.g. increased reliability). The economic benefits for the DER owner arise from energy sales. Hence, for a DER developer maximizing the amount of energy traded, while keeping the system within technical operation limits, is paramount. From a societal perspective the use of renewable energy resources offsets fossil-fuel-based energy and provides a cleaner energy supply.

Distribution networks were designed deterministically for unidirectional power flows, from higher voltages to lower voltages, rather than to accommodate large penetrations of DER. As a result, wrongly located DER, DER whose production is not coincident with demand or DER whose capacity largely exceeds the capacity of the network, has negative effects, such as reverse power flows, increments in line losses and voltage rise [3]. DER located close to fault points contribute to the fault currents and might require the replacement of switchgear equipment [3]. Other impacts of DER include the degradation of voltage quality, by injecting power-electronic harmonics, and an increase in network instability, because of the low inertia of DER [6].

The distribution network must be kept within operational and design limits at all times to provide good-quality energy and avoid damage to the equipment. Hence, the technical impacts of DER can limit the installation of DER and restrict the associated economic and environmental benefits. In weak rural networks, where large amounts of renewable resources are expected to be located, voltage rise [7] and thermal capacity are the impacts limiting the integration of DER. In meshed urban networks, where large numbers of micro-CHP units could potentially be installed, thermal limits and fault levels are the most common constraining factors [3].

There are two management philosophies to keep the network within operational limits and to minimize the steady state impacts of DER: "fit-and-forget" and Active Network Management (ANM). Under a traditional "fit-and-forget" connection philosophy, the grid is reinforced to keep the system within deterministic operational limits. That is to say, the operational problems are solved at the planning stage. Strbac et al. [8] identifies that the "fit-and-forget" approach would require extremely costly reinforcements in the network to accommodate large penetrations of DER. Hence, this management philosophy is limiting for the integration of DER [4]. Thus, "a fundamental shift from passive to active network management" was proposed in recent years [9]. Under this management philosophy the operational problems are solved with the active management of the network and the DER. ANM has been shown to considerably increase the amount of DER that can be connected to the network without the need for reinforcement [4].

Under either management approach, the optimal integration of DER in the distribution grid is fundamental to guarantee the best use of resources, i.e. maximize benefits and minimize costs. The sub-optimal integration of DER under a "fit-and-forget" management will result in a requirement for additional and unnecessary transmission and distribution grid reinforcements, network 'sterilization', increased line losses and/or unattainable development and environmental targets [5,10,11]. Likewise, the sub-optimal integration of DER under active DER management will result in excessive energy curtailment, which could convert an economically feasible project into an unfeasible one [12], and restrict the further exploitation of renewable energy resources.

This paper reviews techniques for the optimal integration of DER. In particular, the area of multi-objective DER planning is examined in detail. In Section 2 the problem formulation is presented, and the dilemma between optimization and modeling discussed, some single-objective techniques are introduced. Section 3 examines the key concepts of multi-objective optimization, and introduces the two main types of techniques used in this area. Section 4 presents the critical review of multi-objective DER planning. A summarizing discussion and conclusions are provided in Section 5.

2. Planning of distributed energy resources

2.1. Problem formulation

DER planning is the structured process of optimizing DER type, size and/or location in order to achieve a set of objectives and subject to a set of constraints. A general representation of this problem can be expressed formally as:

$$\min \mathbf{F}(\mathbf{x}) = \min([f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_m(\mathbf{x})])$$
$$\text{s.t.}$$
$$\mathbf{x} \in \Omega$$
$$\mathbf{G}(\mathbf{x}) = 0$$
$$\mathbf{H}(\mathbf{x}) \leq 0$$

where f_i is the i^{th} objective function; m, the number of objectives; $\mathbf{x}$, the decision vector of DER location, sizes and types; Ω, the decision

domain that defines the possible locations, sizes and types of DER (search space); $\mathbf{G}(\mathbf{x})$, the equality constraints, usually defined by the power flow equations of the network; $\mathbf{H}(\mathbf{x})$, the inequality constraints, usually technical limits of the equipment (e.g. voltage constraints, thermal constraints, short circuit limits, etc.), operating limits of DER (e.g. maximum capacity) or performance targets (e.g. reliability, emissions, maximum allowed curtailment).

This problem has nonlinear equality constraints defined by the power flow equations; hence, it is a non-convex optimization problem. It also has some nonlinear optimization objectives, such as line loss minimization. The planning variables are the discrete locations, sizes and types of DER and the topology of the network. As a result, DER planning is a non-convex combinatorial problem, with several local optima, and one global optimal solution. Non-convex, nonlinear, combinatorial problems are usually difficult to solve using traditional mathematical methods since these methods are designed to find local optima solutions [13].

The complexity of this optimization task is dealt with using two approaches. The first is to apply simplifying assumptions to the formulation of the problem. For example, linearization of the objective functions and constraints, relaxation of the constraints, reduction of the dimensions of the search space, assumption of the discrete nature of DER units as continuous, simplification of the time-variability of load and DER into snapshot analyses [12]. In this way, it is possible to solve the optimization problem using traditional mathematical programming methods, for which powerful programming methods are available (e.g. Linear Programming).

The second approach is based on the use of heuristic optimization techniques, such as Evolutionary Algorithms (EA). These heuristic techniques are well suited to deal with non-convex combinatorial problems [14] and can handle discontinuous search spaces. Moreover, they allow optimization of intricate non-differentiable objective functions. Hence, they enable more detailed modeling of the time-variability of DER. Though, the drawback of these techniques is that they only find an approximation of the global optimal solution in a limited time. This optimization/modeling dilemma is discussed further next. A thorough account of the development and application of heuristics techniques within power systems problems is given in [15].

2.2. DER planning: an optimization/modeling dilemma

When a real optimization problem, such as DER planning, is over-simplified the optimal solutions found are in fact sub-optimal, or as phrased by Irving and Song [16]: “a real solution to a non-problem”. For instance, a simplistic model of renewable generators (e.g. a snapshot power-flow analysis, or the analysis of a single-day profile for wind generation) optimized with a very accurate optimization method (e.g. linear programming) will produce solutions that although accurate, will almost certainly be sub-optimal for the real problem, given the limited scope of the model. Similarly, a realistic model of DER is worthless when optimized with an inaccurate optimization method, i.e. “a non-solution to a real problem” [16]. For example, an extremely complex model of the power system (e.g. a minute-by-minute simulation of the power system) optimized by an ad hoc method (e.g. analysis of a few configurations chosen by hand) will clearly provide a solution that is not optimal, even with the realistic model used. These examples illustrate the optimization/modeling dilemma faced in the solution of real optimization problems (Fig. 1). Hence, if useful planning tools are to be produced for DER planning, the formulation of the problem should be as close to the upper-right corner of the figure as possible. Often, this requires a good compromise between the accuracy of the optimization method, and the detail of the model of DER and the network.

There are some key aspects that need to be considered when modeling the DER planning problem. First, some benefits and impacts of DER depend not only on the location and size of the generation, but also on the complex relationship of generation and demand over time. The interaction of diverse time-variant energy sources and demand is stochastic in nature. Adequate evaluation

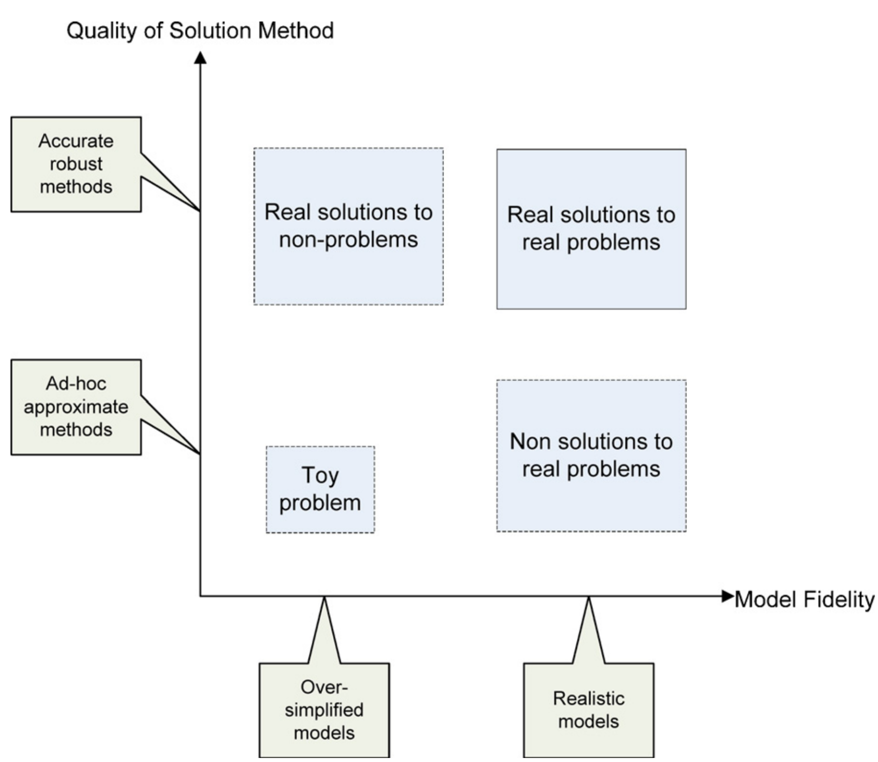

Fig. 1. Optimization/modeling dilemma. Adapted from [16].

methods, such as probabilistic load flow [17], stochastic simulation or Monte Carlo Simulation [18], can be used to evaluate the interaction of stochastic DER and demand.

Also, network access for DER has been traditionally allocated on a firm access basis. In this case a "worst-case scenario" analysis of maximum generation and minimum load is sufficient to evaluate some of the impacts of DER. However, some renewable generators, such as wind turbines, provide their maximum output for only very short periods of time [19], and as a result the use of a probabilistic analysis of DER integration provides a more objective evaluation of DER impacts and benefits [4].

Moreover, recent studies have shown that a non-firm integration of DER permits larger renewable energy production [20]. When non-firm access is considered, active management of the DER and the network is essential to minimize the network impacts and avoid expensive network reinforcements [4,21]. The modeling of the DER planning problem becomes more complex when the evaluation of controllable technologies is proposed.

A simplified deterministic approach limits the analysis of time-variant energy resources (e.g. wind and solar energy), or the consideration of controllable technologies (storage, ANM). Consequently, the optimal integration of DER must determine not only the optimal number, size and location of DER units, but also evaluate stochastic impacts of DER, and the possibility of actively controlling DER and the network.

2.3. Single-objective DER planning

In recent years diverse methods for optimizing the location, size and/or type of DER have been proposed, with particular emphasis on DG placement and sizing. Most DER planning methods focus on the optimization of a single objective. Some examples of single-objective methods are discussed next. One of the most common objectives found in literature is the minimization of line losses. Line loss minimization methods are based on analytical optimization techniques (e.g. [22]), mathematical programming techniques (e.g. [23]) and genetic algorithms (e.g. [24]). For simplification, few of these methods consider the stochastic nature of DER. Moreover, none of these techniques considers the impact of active networks in the analysis.

Other single-objective DER planning approaches focus on the minimization of total cost. Cost can be aggregated from different points-of-view. Hence, these techniques formulate the problem either from the perspective of a DER developer [25], from the perspective of a DSO that can invest in DER [26,27] or from the perspective of a DSO that cannot invest in DER and wants to minimize the cost of network reinforcements [28]. These methods are based on the use of traditional mathematical optimization techniques and genetic algorithms.

More recently, methods to quantify the network capacity, i.e. how much DER can be optimally connected without the need of reinforcements, have been proposed. These methods respond to the need to increase renewable DER installations at the minimum cost. For instance, Harrison and Wallace [11] present an Optimal Power Flow (OPF) approach to obtain the maximum DER capacity in predefined locations. This method was later upgraded to optimize both DER locations and size simultaneously, using a hybrid "GA-OPF" approach, where the Genetic Algorithm (GA) is used to solve the combinatorial problem, and the OPF solves the capacity allocation problem [29]. Keane and O'Malley explore a similar problem, and propose a linear programming technique to find the maximum capacity the can be installed using a firm connection [30], or to maximize the energy that can be harvested, minimizing network violations, in a non-firm integration [20]. Ochoa et al. [31] take the problem further, and propose a multi-period OPF to maximize the DER capacity that can be installed considering ANM. This method is based on non-linear programming. It allows the analysis of stochastic DER, and could be updated to maximize energy harvesting, instead of installed capacity.

A single-objective approach is often practical from a DER developer or a DSO point-of-view. DER developers can obtain information about the most promising locations for DER investments to maximize installed capacity, energy sales and revenue. Also, even if DSOs are not allowed to own and operate DG, as in most European counties, they can identify which locations, sizes and types are beneficial (or detrimental) for their system operation, and provide incentives for optimal network development [32].

2.4. Multi-objective DER planning

Diverse stakeholders participate in DER development and management. Hence, planning objectives can be formulated from different perspectives, e.g. the DER developer, the DSO, or civil society, ideally represented by the regulator [33]. Some of the DER planning objectives are naturally conflicting; consequently in some cases there is no single planning solution that will satisfy all stakeholders. For example, DER capacity maximization will produce an increase in line losses [34]; likewise, cost minimization of network investments conflicts both with capacity maximization and line loss minimization. Similarly, society's interest in low-carbon energy sources might conflict with the need for an affordable and reliable energy supply. A multi-objective approach helps to identify compromise solutions that benefit all stakeholders [34]. Moreover, multi-objective DER planning methods can provide valuable information about the correlations between the benefits and impacts of DER integration, and can inform the decision-making process [35]. From a high-level perspective, a multi-objective analysis of DER integration can help to inform incentives and policies to encourage DER developments in the places, sizes and types that ensure benefits and minimize the impacts of DER. Next, the key concepts of multi-objective optimization are discussed, and the main types of multi-objective optimization methods introduced.

3. Multi-objective optimization

3.1. Key concepts

When an optimization problem has a single objective the definition of "best solution" is one-dimensional and there is only a single best solution (or none, eventually). In contrast, a multi-objective problem with conflicting objectives has no single solution, but a set of optimal solutions. In this case, the multi-dimensional concept of "dominance" is used to determine if one solution is better than other solutions. A solution a is said to dominate a solution b if the following two conditions are true [36]:

- a is no worse than b in all objectives and
- a is better than b in at least one objective.

In this case b is said to be "dominated" by a, or alternatively, a is said to be "non-dominated" by b. A dominated solution is also said to be "sub-optimal". The solution to the multi-objective problem is the set of non-dominated solutions, known as the Pareto set. In terms of their objectives the Pareto set is referred as to the Pareto front, and these terms are sometimes used interchangeably. A solution belongs to the Pareto set if no improvement is possible in one objective without losing in any other objective. These concepts are illustrated in Fig. 2.

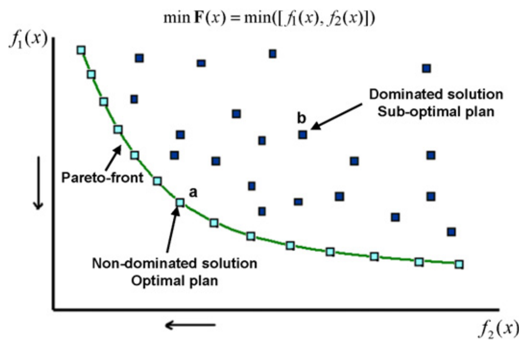

Fig. 2. A Pareto-front for a two-objective problem.

Finding a single solution for a multi-objective problem involves two stages: optimization and decision-making. Depending on the order in which these tasks are performed, there are two possible approaches to obtain a single solution for a multi-objective problem, as illustrated in Fig. 3. The first approach uses *a priori* preference information and single-objective optimization techniques. All objectives are aggregated into a single-objective function that is optimized (e.g. weighted-sum method), or alternatively, one 'master' objective is optimized and the rest of the objectives are considered as constraints. In these two cases the decision-making process precedes the optimization process (e.g. left-hand side of Fig. 3). These procedures can be very useful to find single solutions when detailed preference information is known *a priori* [36]. Deep knowledge of the problem is required to define an adequate aggregation method and weights, or master objectives and constraint levels, respectively.

When *a priori* information is not easily available, the process of obtaining as many solutions as possible in the Pareto set, i.e. *the multi-objective optimization process*, is critical. The information contained in the Pareto front elucidates compromise solutions between different stakeholders or trade-offs between incommensurable objectives. This knowledge facilitates a more informed decision-making process and provides deep insight into the problem. As a result, in the second approach the decision-making process takes place after the multi-objective optimization (e.g. right-hand side of Fig. 3). Initially, several solutions of the Pareto front are sought at once, and preference information is expressed afterwards (*a posteriori*). Some authors believe the second approach to be an "ideal" (or "true") multi-objective optimization approach for the following reasons:

- The method is more methodical, more practical and less subjective, compared with *a priori* approaches [36].
- It provides a wider range of alternatives to choose from, information that would have been lost is conserved; therefore, it permits more informed decisions [37].
- Since real problems are usually multi-objective, this approach permits a more realistic representation of practical problems [37].
- Through transparency the approach permits the generation of useful information about the problem being studied [38]; it is

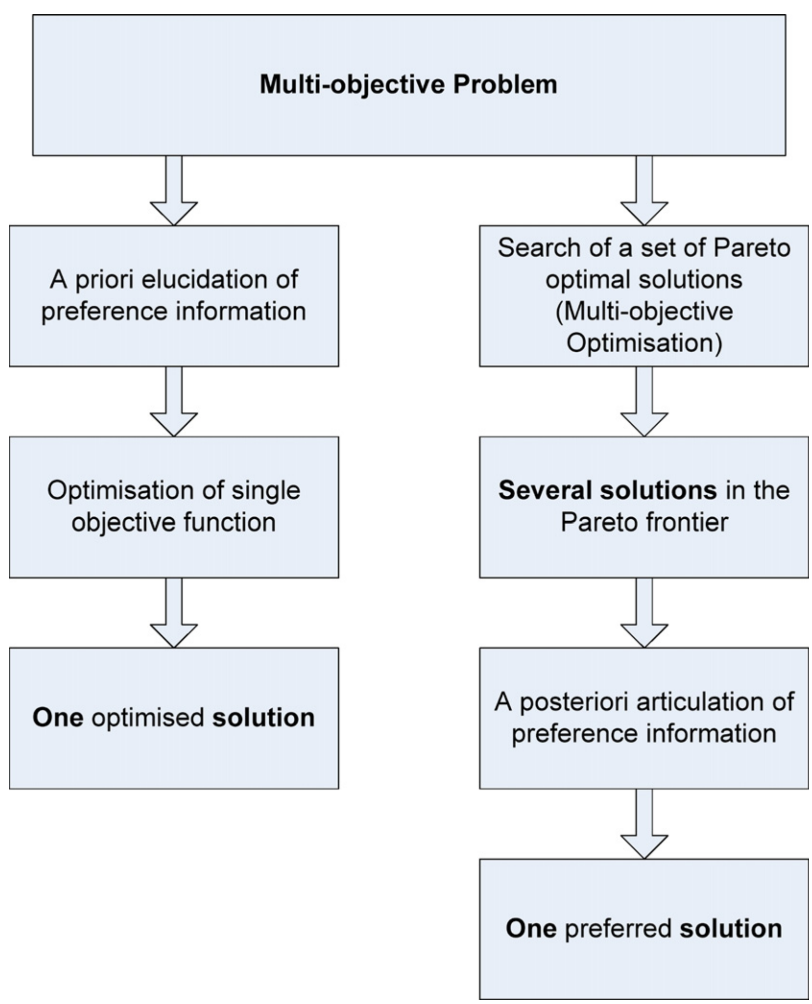

Fig. 3. Finding a single solution for a multi-objective problem.

possible to know the scope of every objective and to analyze the correlations between objectives.

Next, multi-objective optimization methods used to find the Pareto set are introduced. This introduction provides a theoretical background for the literature review of Section 4.

3.2. Multi-objective optimization methods

Normally, multi-objective problems have a large number of solutions defined by the Pareto front. Since finding all Pareto solutions is practically impossible, a subset of the Pareto set is usually looked for. Hence, multi-objective optimization is the process of finding as many solutions of the Pareto front as possible. Solving a multi-objective problem involves satisfying three areas [36,39]:

- *Accuracy*: To find a set of solutions as close to the real Pareto front as possible.
- *Diversity*: To find a set of solutions as diverse as possible.
- *Spread*: To find a set of solutions that "capture the whole spectrum" of the true Pareto front.

These requirements are exemplified in Fig. 4. The first case (Case 1) is able to obtain solutions that are accurate and capture the extent of the objectives; nonetheless, the set of solutions is not diverse. In the second case (Case 2), a diverse set of well-spread solutions is obtained, although these are not accurate. The solutions in the third case (Case 3) are accurate and diverse; however, the edges of the Pareto front are not explored. Finally, the fourth case (Case 4) illustrates the solution of an ideal algorithm.

Methods to find several Pareto set solutions are divided into two main groups [36]. The first group makes use of single-objective techniques and *a priori* information. Several solutions of the Pareto set are identified by changing the aggregation function or the master objective iteratively. The use of single-objective optimization methods for multi-objective optimization is known as the "classical approach" to multi-objective optimization. Two of the most common methods of this type are the weighted-sum method and the ε-constrained method [36]. These methods can be very useful when detailed preference information is known beforehand. However, these methods have their drawbacks, the weighted-sum method can prove to be very time consuming with a large number of objectives (i.e. a large Pareto set) and the solutions found will strongly depend on the shape of the Pareto frontier and the aggregation method [36]. Also, the weighted-sum method is unable to deal with non-convex Pareto fronts. Similarly, the ε-constrained has been classified as a "naïve" approach for multi-objective optimization [40], as it requires strong *a priori* knowledge of the problem [41], is time consuming (each single solution of the Pareto front requires several iterations) and it is not appropriate for a large number of objectives [41].

The second group of multi-objective optimization methods is based on Evolutionary Algorithms [36]. EA handle sets of possible solutions simultaneously, and as a result, permit identification of several solutions of the Pareto front at once. Hence, EA are recognized as a natural way of solving multi-objective problems efficiently. The first Multi-objective Evolutionary Algorithm (MOEA) was proposed in 1984. Since then, a large number of MOEA has been developed. Generally, these are classified as first-generation or second-generation MOEA [36]. The key characteristic

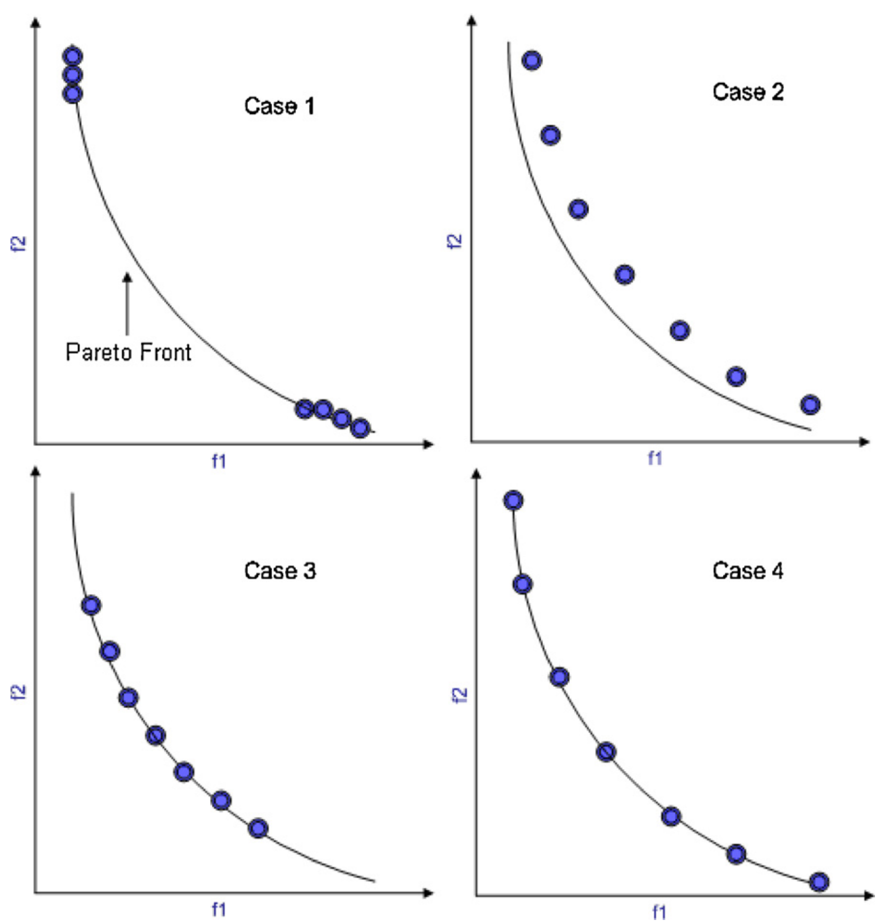

Fig. 4. Requirements of a multi-objective optimization problem.

of the second generation of MOEA is the use of elitism. Second-generation MOEA have been demonstrated to outperform their first-generation (non-elitist) counterparts [36]. A detailed account on the development of MOEA is presented in [12,36]. At present, two of the most recognized algorithms of the second generation are the Non Sorting Genetic Algorithm II (NSGA-II) [42] and the Strength Pareto Evolutionary Algorithm 2 (SPEA2) [43]. These algorithms include procedures to find an accurate, diverse and well-spread Pareto front. Hence, they guarantee to generate useful information for the subsequent decision-making process.

A growing number of authors have proposed multi-objective approaches for the DER planning problem, especially in the last six years. Initially, "classical" multi-objective optimization techniques were used. Then, the recognition that a "true" multi-objective approach provides a better way of solving the problem encouraged the use of specialized MOEA such as the ones aforementioned. In the next sections, these multi-objective DER planning approaches are reviewed. They have been grouped based on authors (or research groups) and this can be read as the 'schools' from which this thinking on DER planning optimization is emerging.

4. Multi-objective DER planning: a review

4.1. From the ε-constrained method to the NSGA-II method

Celli et al. [32] presented in the 2003 Power Tech Conference one of the first works to discuss the advantages of a multi-objective formulation for DG planning. This work proposes the use of a GA based ε-constrained method to find the best sizes and locations for DG to minimize several objectives. These objectives are: cost of reinforcements, cost of energy non-served, cost of power losses, cost of energy bought and a harmonic distortion index. In addition, technical constraints of the network are taken into account (voltage, line current and short circuit limits). The problem is analyzed from the point-of-view of a DSO that has no control over DG investments. Hence, Celli et al. mention that the information produced by the planning tool can be used to determine any incentives the utility could offer to DG developers.

This work was later extended and published in 2005 [35]. In this second publication, Celli et al. discuss load and DG variability. The objective function is evaluated by means of a probabilistic load-flow, previously developed by Celli et al. [44]. It can be inferred that this approach was also used in the publication reviewed in the previous paragraph. This probabilistic load flow assumes linear correlations among DG units, and between loads and DG units. Therefore, controllable DG units cannot be analyzed with this method. The probabilistic load flow used assumes that the probability distribution function (PDF) of all generators and loads is normally distributed. However, some DER cannot be accurately described by a normal PDF. For example, wind energy is usually described using Weibull or Rayleigh distributions [10]. Hence, in some cases the evaluation of planning attributes using this approach will be only approximated.

In 2005, Carpinelli et al. [45] extend the multi-objective approach in order to include uncertainties in DG energy production. Each one of the possible futures is formulated as a scenario. Subsequently, a "double trade-off method" is used. The double-trade-off method can be summarized in five steps:

1. Formulate the problem as a single-objective problem: use one objective of interest for the planner as the master objective, and the rest of the objectives as constraints.
2. For each objective chosen and for each scenario, apply the ε-constrained method [35] to find several Pareto solutions.
3. Evaluate the set of optimal solutions of each scenario in the remaining scenarios.
4. For each scenario, determine the set of non-dominated alternatives (conditional set).
5. Finally, find the global decision set: the alternatives that are not dominated in at least one future, that is, the union of the conditional sets.

The robustness of each of the alternatives in the global decision set is calculated and used to choose the best plans. The robustness of an alternative is defined as the proportion of scenarios where it belongs to the conditional set. That is, the alternatives with the highest robustness are those which belong to the Pareto front in most of the possible futures (scenarios).

The double-trade-off method is based on the trade-off analysis proposed by Burke et al. in 1988 [46] and it is a practical way to deal with uncertainties under a multi-objective perspective. The scenario technique is considered by Willis [47] as the only valid method to handle future uncertainties, especially in multi-objective problems. The work of Carpinelli et al. [45] analyses three minimization objectives: cost of energy losses, voltage profile and total harmonic distortion. The voltage profile objective is calculated as the mean deviation of voltage across the network. However, this might obscure localized benefits of DG, or alternatively, hide problems that are not solved by DG.

Subsequently in 2007, Carpinelli et al. [48] apply the double trade-off approach to the optimal sizing and siting of power-electronic interfaced (controllable DG). An inner optimization is used in every evaluation step of the Genetic Algorithm to determine the best operation mode of the power-electronic interface. This inner optimization has the objective of reducing harmonic distortion and improving voltage profile by managing reactive power. In this approach, the variability of DG is not addressed. Though, importantly, this paper illustrates the possibility of GA to accommodate inner optimization algorithms to handle controllable DER. It proposes the use of reactive power management to control voltage profiles. Nonetheless, because of the high R/X ratio of distribution lines, voltage magnitudes are also dependant on active power injections [49]. Hence, active power management of DG/DER could also be considered to manage voltage profiles [50].

Until 2008, largely all the multi-objective formulations proposed by the power systems research group of the University of Cagliari were based on the ε-constrained method. In Carpinelli et al. [45] the authors already recognized that *a priori* preferences could notably affect the final solutions. Moreover, in the 2008 PMAPS conference, Celli et al. [51] acknowledged that the use of true multi-objective approaches seems more effective than the ε-constrained method. So, in this latter work [51] the planning approach previously proposed in [35] is updated to a state-of-the-art Multi-objective Evolutionary Algorithm (NSGA-II [42]).

Celli et al. [51] also propose a problem formulation that can handle different types of generators simultaneously, and can incorporate optimization constraints using the concept of "constraint-dominance", proposed by Deb et al. [42]. Constraint-dominance extends the concept of dominance, discussed at the start of Section 3. A solution *a* is said to "constraint-dominate" a solution *b*, if any of the following conditions is true:

- Solution *a* is feasible and solution *b* is not.
- Solutions *a* and *b* are both infeasible, but solution *a* has a smaller overall constraint violation.
- Solutions a and *b* are feasible and solution *a* dominates solution *b*.

This concept provides a useful and parameter-less constraint handling technique that can be applied to other Multi-objective Evolutionary Algorithm.

Celli et al. [51] recognize that one of the drivers for DG is the environmental benefits that some DG technologies can provide; so, an environmental objective (minimization of total CO_2 emissions) is explicitly included. Hence, in this work, the authors provide a comprehensive formulation of the problem from the DSO perspective, which includes technical, economic and environmental objectives. DG and load time-variability are acknowledged, and DG production and load is evaluated using a probabilistic approach although, in the case study presented in the paper only simplistic daily load curves are used, ignoring seasonal variations of DG and load.

In the 2009 CIRED conference Celli et al. [33] argue, realistically, that DG investments are not decided by DSOs, in the current regulatory environment. As a result, they propose a multi-attribute analysis of random DG configurations. In this analysis no optimization is performed, but the dominance relationships between thousands of random solutions is evaluated to determine a sub-optimal Pareto front. Three objectives are chosen, one to represent the DSOs perspective, another one representing the DER developer point-of-view, and one representing civil society. Importantly, they incorporate diverse ANM schemes into the analysis. However, the probabilistic representation of wind production is simplified as a normal distribution, which will only provide approximate results, as already discussed at the start of this section. The multi-attribute analysis of random configurations provides a more realistic picture of possible DER developments. However, the optimization of DER configuration could inform DSOs and the regulator to encourage developments in an optimal manner, as initially discussed by Celli et al. [32].

In summary, through all the publications reviewed Celli, Carpinelli et al. highlight the advantages of using a multi-objective approach; they recognize that a multi-objective approach permits a better simulation of reality and that it can help in the decision-making process. They mention a key aspect: "a (planning) tool should leave the planner the faculty of choosing which aspects to consider in his search of the optimal solution" [35]. These publications brought the research community's attention towards the multi-objective nature of the DER planning problem. As a result, [35] is frequently cited in recent works in the area. Conversely, these approaches have some limitations. For example, the probabilistic approach used [44] cannot handle controllable DER units, and provides only an approximated representation of wind generation. Furthermore, while probabilistic information is available, the use of the probability of constraint violation as a planning objective/constraint is not investigated, even when new regulations favor the use of probabilistic treatment of constraints, for example the European Standard EN 50160 [52].

4.2. A multi-objective performance index

The work of Ochoa et al. [53] focuses on the technical impacts of DG. In 2005 the authors propose the use of a "multi-objective performance index" to evaluate various technical impacts of DG in unbalanced distribution networks: active power losses, maximum voltage drop and short circuit currents. This performance index is calculated as a weighted-sum of these technical impacts. In order to find the best locations for DG connections in distribution networks, Ochoa et al. [53] propose the use of a single-objective GA, and employ the weighted-sum index as the objective function. In this was the best locations that minimize DG impacts are determined. This paper recognizes that DSOs might not have control over DG investments, but that information about optimal DG locations could shape the nature of the contract between the DSO and the DER developer.

Subsequently, Ochoa et al. demonstrate the applicability of the multi-objective performance index to single DG/load scenarios [54] and to scenarios that include time-varying generation [55]. The analysis of two additional impacts is added: reserve capacity of conductors and reactive power losses. However, in both of these papers, the approach is limited to an evaluation of possible DG connections (exhaustive location of DG units in diverse nodes), rather than applying an optimization algorithm to find the best locations/sizes for DG. Even so, the approach is a powerful tool for DG impacts evaluation as it considers unbalanced networks, load and DG variability. Moreover, the authors acknowledge that other impacts (economic and environmental) could be included in the evaluation.

The multi-objective index evaluates several impacts. However, in the case of radial networks (as are most distribution networks in normal operation), it can be demonstrated that most of the impacts have a high positive correlation. For example, active and reactive line losses are concurrent. Similarly, line losses (active and reactive) and reserve capacity of conductors both depend on line flows. Likewise, line losses and maximum voltage levels have a positive correlation. As a result, the weighted-sum is measuring several times the same basic effect, i.e. the reduction of line flows. A "true" multi-objective formulation of the problem, explained in a previous section, and an analysis of objectives correlation (e.g. by means of Principal Component Analysis [56]) could identify these relationships and determine the minimum number of impacts that need to be analyzed [57].

The multi-objective index is a weighted-sum of the technical impacts; that is, a single value that represents not only the technical impacts of DG but also the point-of-view of the planner. The implications of using this weighted-sum are discussed in Ochoa's doctoral thesis [58], published in 2006. In this work, it is discussed that the major drawback of the weighted-sum approach is the difficulty of determining appropriate values for the weights when there is not enough information about the problem. So, Ochoa proposes a true multi-objective formulation of the problem. In this case, the first-generation Non Sorting Genetic Algorithm (NGSA) is used to locate a small number of fixed size wind turbines in order to maximize/minimize energy exports (for profit or energy independence, respectively) and minimize energy losses and short circuit limits. In this way, it is possible to investigate a compromise between DG benefits, and impacts. Ochoa mentions that while more objectives could be included in the formulation, care must be taken to guarantee that objectives are not concurrent.

The multi-objective index proposed by Ochoa et al. [54] was recently applied by Singh et al. [59] to investigate the effect of five different load models on the optimal placement of DG. This study used a snapshot analysis of the system, with a simplified representation of DG (constant power, at unity power factor). Results showed that different optimal locations and sizes were obtained with different load models. It concluded that the load model has "a decisive role" on the optimal placement and sizing of DG, demonstrating the importance of using an accurate model of the system being studied.

4.3. Multi-objective planning of stochastic DER and storage

Haesen et al. [60] discuss the drawbacks of single-objective formulations and recognize the advantages of a true multi-objective approach. Accordingly, in 2006 Haesen et al. [60] propose a multi-objective DER optimization based on the first-generation Strength Pareto Evolutionary Algorithm (SPEA). The objective function evaluation includes a simplistic simulation of daily DER production and load profiles; though the method permits the optimization of several types of DER simultaneously. This multi-objective DER planning approach is compared with the iterative use of a single-objective method, previously proposed by Haesen et al. [61]. The comparison shows that single weighted-sum

solutions are better than the ones found in the Pareto front by SPEA, but that in contrast the whole Pareto front provides a wider range of possible solutions to choose from. Also, each weighted-sum solution is highly sensitive to the set of parameters chosen. Therefore, if a single solution is sought, inaccuracy in any weight will lead the search towards mistaken regions of the Pareto set and produce a sub-optimal plan. As a result, Haesen et al. suggest the use of both methods to gain insight into the planning problem. However, finding each single weighted-sum solution requires as many iterations as finding the whole Pareto front using SPEA.

Importantly, in this work, Haesen et al. recognize that in cases when attributes cannot be converted to cost accurately, when all costs cannot be aggregated into a single parameter or when a larger number of objectives are analyzed, the "true" multi-objective optimization becomes essential. This argument is exemplified by a case study that analyses four very distinct planning objectives: line loss minimization, minimization of the main grid energy flow (as a proportional measure of reliability), DER installation cost and the gas distribution grid investments. Finally, this paper proposes the use of bi-objective plots [36] to examine correlations or conflicts between objectives. This visualization technique becomes extremely useful when the number of objectives is greater than three.

In the next paper of Haesen et al. [62], the use of traditional mathematical optimization techniques for planning time-variant DER is studied. The DER planning problem is formulated as an iterative Mixed Integer Quadratic Programming problem. Traditional optimization techniques require mathematical formulations of the objective functions. These formulations can only include deterministic profiles. As a result, the authors conclude that traditional optimization techniques cannot model the stochastic aspects of DER and load effectively. In addition, the authors identify that some objectives (e.g. voltage sags, reliability) cannot be formulated as a mathematical function of DER type, placement and size.

As a result, Haesen et al. [62] highlight that GA can handle objectives that are too complex to be reasonably formulated in an analytical expression. So, the use of Monte Carlo Simulation (MCS) in the objective evaluation is suggested, instead of the daily profiles simulation used in [59]. The MCS method produces an accurate evaluation of the stochastic performance of DER (e.g. wind production) and load without the need for an analytical formulation. Moreover, it permits the evaluation of other objectives that are difficult to formulate analytically (e.g. reliability). In the approach proposed, MCS consists of the simulation of a number of different yearly profiles. The planning methodology for stochastic DER is summarized in a further paper [63] published in 2007. In this work, the authors recognize that an optimization approach should be as adapted to the problem as possible, a clear reference to the optimization/modeling dilemma already discussed.

The GA-MCS approach provides a practical way of evaluating topologies with stochastic DER, however two trade-offs can be identified. First, the optimization/modeling trade-off [15]: GA permit the evaluation of more realistic models, but the convergence towards global optima cannot be reached in limited time. In contrast, analytical expressions are able to find the global optima (with appropriate parameters), yet, they are limited to evaluate simplified models. The second trade-off relates to the accuracy of the MCS. The accuracy of MCS evaluations depends on the number of trials or years simulated [18]. So, accuracy improves but to the detriment of the speed of the GA, and vice versa. Though, the GA-MCS evaluation time needs to be put in perspective. First, planning is not an "online" task and optimization studies can be performed at the same time as other studies. Second, and more importantly, it is possible to get results and insights that otherwise would have never been obtained.

The SPEA planning approach is used by Haesen et al. [64] to analyze the incorporation of a single controllable energy storage unit into a distribution grid with stochastic DER. This work was presented in the CIRED 2007 conference. In this case, an inner optimization algorithm is used in the objective evaluation stage of the GA to optimize the operation of the storage unit. Simultaneously, the external multi-objective optimization is used to optimize the rating (power) and capacity (energy) of the storage unit. This inner optimization offers a practical method to optimize controllable energy storage *when DER units are already installed*. However, the approach is not able to optimize stochastic units that can be controlled (e.g. curtailment of wind generators, dispatch of CHP units), or the simultaneous optimization of stochastic and controllable units.

In the CIRED 2007 conference presentation [65], Haesen proposed the use of Principal Component Analysis (PCA) [66], a powerful method to reduce the dimensions of a multi-objective problem and analyze multiple objective correlations. Moreover, Haesen et al. [64] explore the use of probabilistic measures of DER impacts; it uses the 95-percentile of the probability distribution for the maximum voltage deviation as one of the planning objectives.

In summary, the method proposed by Haesen et al. permits the multi-objective optimization of diverse types of time-variant DER or controllable energy storage. It provides a flexible platform in which different planning objectives can be formulated. Though, it is not possible to infer from the works published how network constraints are treated in the multi-objective formulation. No constraint management under the multi-objective formulation is described.

4.4. A multi-objective planning framework for controllable and stochastic DER

In a work published in 2009, Alarcon-Rodriguez et al. [50] extend the framework proposed by Haesen et al., reviewed in the previous section. Alarcon-Rodriguez et al. [50] present a flexible planning framework for optimizing controllable and stochastic DER. The method has three key elements:

- An outer multi-objective optimization algorithm based on the second-generation SPEA2. Previous studies had shown that the SPEA algorithm is outperformed by both the NSGA-II [42] and SPEA2 [43].
- A stochastic simulation algorithm for the evaluation of stochastic DER.
- An inner optimization algorithm for the evaluation of controllable DER, formulated as a linear Optimal Power Flow.

In this work, the formulation of the outer optimization algorithm (SPEA2) permits the optimization of different types of stochastic and controllable DER simultaneously. The stochastic simulation algorithm permits the evaluation of stochastic DER, either using historical data of DER production, or using weather models to produce this data. The accuracy of the stochastic evaluation will depend on the number of events evaluated [18]. Hence, accurate evaluations will require longer computation times. The inner OPF can be adapted to evaluate energy storage or different ANM schemes (e.g. active power dispatch, reactive power dispatch, active voltage control). Moreover, Alarcon-Rodriguez et al. [50] use the probability of voltage violations in the system as one of the planning objectives. It has been suggested that a probabilistic analysis permits a more objective evaluation of DER impacts [4]. In addition, the minimization of carbon emissions is explicitly formulated as a planning objective. Previous work of Alarcon-Rodriguez et al. presented in 2006 [67] and published later in 2008 [68] proposed a multi-attribute analysis of DER, using

a MCS evaluation, with a flexible treatment of constraints, and the explicit formulation of environmental objectives.

Other planning objectives considered in the case study in [50] are: the minimization of line losses, the minimization of extra energy dispatch, the minimization of energy curtailment, and the minimization of the DER penetration level. This last objective might seem counterintuitive, as single-objective techniques aim to maximize DER penetration; nonetheless, it is necessary in a multi-objective approach to determine the optimal attainment level of each of the planning objectives for each level of penetration of DER [12].

The planning framework proposed in [50] was extended by Haesen et al. [69] to compare network reinforcement and DER as alternative planning options. The effects of different tariff schemes in the objectives of the DSO and DER developers were examined. This work was presented in 2009. The concept of constraint-dominance, already discussed in a previous section, was incorporated in the SPEA2 fitness evaluation step. Constraint-dominance permits the formulation of any planning attribute as a planning constraint, extending the flexibility of the framework. In the case study presented by Haesen et al. [69], the use of probabilistic constraints is proposed, following recent European Regulations. The EN50160 Power Quality norm which has to be guaranteed by the DSO in many European countries requires the grid voltage at LV to remain within 10% of the nominal voltage for 95% of the time [52].

In summary, the planning framework proposed by Alarcon-Rodriguez, Haesen et al., which is extensively discussed in [12,70], provides a flexible platform, in which diverse impacts of DER integration can be analyzed, either as planning objectives or planning constraints. Probabilistic measures of DER impact can be evaluated, and any number of DER types can be incorporated in the analysis. The framework can be modified to analyze different ANM schemes.

A drawback of the proposed methodology is that it is inherently computationally expensive. Though, this can be said of any approach based on EA with inner MCS objective evaluations, as mentioned in a previous section. SPEA2 requires the evaluation of thousands of potential solutions (i.e. chromosomes) to obtain a good approximation of the Pareto set. At the same time, the stochastic simulation of each chromosome requires from hundreds to thousands of evaluations to get accurate estimations of the planning attributes. Moreover, OPF evaluations (for controllable DER units) tend to take more than simple power flows to analyze uncontrollable units. Though, this long evaluation time needs to be considered in perspective, as already discussed, the method enables to produce information that cannot be obtained with simplified approaches.

4.5. Other multi-objective approaches

The methods reviewed next do not belong to any of the "schools" previously introduced. Their key contributions and limitations are highlighted:

Pelet et al. [71] study the optimization of the design parameters of an integrated energy system (diesel and PV generators) for a remote community. Detailed analytical formulations are used for the diesel engines and PV operation, cost and emissions calculation. Two objectives are used: total cost and CO_2 emissions. The authors use a "true" multi-objective formulation, based on a second-generation MOEA. They argue that keeping the two objectives separated enables more informed design decisions, as it is possible to find and rank the best integrated solutions, which are both cost effective and less polluting. Moreover, the conflict between cost and environmental benefits is recognized with the conclusion that clean solutions are more expensive.

Harrison et al. [34] use the OPF approach presented in [11] to evaluate the incentives provided to DSOs and DER developers for loss reduction and reinforcement deferral. Two different objective functions are analyzed. Each one reflects the point-of-view of a DG developer and a DSO, respectively, both trying to maximize their net benefits. A multi-objective formulation based on the ε-constrained method is presented. Moreover, a multi-period OPF is proposed, which evaluates a load duration curve to provide a better estimation of losses. Harrison et al. show that DG developers and DSOs have conflicting objectives and that a multi-objective formulation can effectively replicate different perspectives of the DG planning problem. Moreover, this work demonstrates that incentives do have a major impact on stakeholders' optimal locations and sizes for DG. For example, DG developers are not directly exposed to the effect of losses, so they try to maximize capacity and profit. On the other hand, DSOs have a loss reduction incentive that outweighs the benefit of connecting DG. Subsequently, they would prefer smaller DG investments that provide a larger reduction in losses, to the detriment of a DG developer's profit. A trade-off analysis enables the identification of several possible compromise solutions. A similar analysis is made for reinforcement deferral incentives. A limitation of the proposed approach is that DG is considered as a firm supply of energy, operating constantly at rated power. This restricts the analysis of time-variant generators such as renewable DG and heat-led CHP. In addition, the ε-constrained method has some drawbacks, which were already discussed.

Mori and Yamada [72] present an approach based on SPEA2 to optimize *distribution network expansion planning*. This approach considers DG as an option for the planner, together with possible substations and lines. It aims at minimizing three objectives: power losses, cost of new equipment and voltage deviation. The cost objective only considers installation costs and it does not take into account operating costs of DG (fuel, O&M). So, the optimal solution could be more expensive in the long-term. In addition, the problem disregards the time-variability of DG. The whole planning exercise is made in terms of peak power. As a result, only a single type of DG can be handled by the formulation (i.e. constant power). Nonetheless, an important point of this work is that it demonstrates that SPEA2 provides better solutions than NSGA-II in the case study presented, although SPEA2 computational time is slightly higher than NSGA-II.

Haghifam et al. [73] also assume that DG is a constant power source. The authors propose an approach based on NSGA-II. The planning objectives include total cost (net present value of energy bought from the transmission system, DG installation and operation), technical and economic risks. The novelty of this work is that it proposes to minimize the maximum risk of constraint violation as one of the planning objectives. In this case, load behavior uncertainty is modeled using fuzzy numbers. The risk of voltage constraint violations is calculated as the fuzzy possibility of voltage constraint violation. The economic risk is treated similarly: the uncertainty of market price of energy is modeled using fuzzy numbers. Then, the fuzzy possibility of DG being a more expensive solution is calculated and minimized. Fuzzy numbers permit the representation of uncertain variables for which limited information is available. Therefore, a quasi-probabilistic formulation of the problem is possible. An analogy can be made between the fuzzy "possibility" of constraint violation and the more elaborated "probability" of constraint violation. However, the calculation of this latter requires more detailed information about the load behavior (e.g. load curve duration, load profile, load model).

Ahmadi et al. [74] also propose to use the NSGA-II algorithm to find the optimal combination of DG units in a network. Three planning objectives are optimized: to minimize total cost, to minimize line losses and to improve voltage profile. Though, the

approach is simplistic. The case study mentions five types of DG, including PV generators, though, the time-variability of DG is not mentioned in the paper, nor modeled in the approach proposed. Since only snapshot analyses are used results can be expected to be unrealistic.

Zangeneh et al. [75] base the optimization on the NSGA-II method. The approach includes the minimization of economic objectives: the total cost of DER installation and operation, the cost of losses and the cost of extra purchased power. It also formulates an environmental objective: the maximization of avoided emissions. In addition, this work outlines a simple methodology for choosing a single solution from the Pareto set, i.e. the decision-making process, discussed in the next section. After the optimization, all objectives are aggregated into a single parameter. Hence, the multi-objective problem is formulated from the perspective of a DSO that can invest in DER as a planning option. It also includes a budget constraint, reflecting that the planner must make the best use of scarce resources. Although the authors decide to use numerically similar weights, it is clear that the weights could reflect the planner's preferences more strongly. Monte Carlo Simulation is proposed as a means to evaluate the uncertainty in some parameters, such as DER costs and energy prices, prior to the decision-making process. This use of MCS must not be confused with the use of MCS to evaluate the stochastic behavior of DER, mentioned in previous sections. A critical shortcoming of this work is that it does not model the variability of DER. It fails to acknowledge that some DER, such as PV and wind turbines, might not be available at peak demand times with any level of certainty.

4.6. Multi-criteria decision-making methods

The review of the previous sections shows that most of the approaches aim at generating a large number of non-dominated solutions, namely the multi-objective optimization process. The decision-making process of choosing correct *a priori* weights or selecting a single solution *a posteriori* is only explored briefly, or not mentioned at all. Several decision-making techniques exist in literature. When a number of attributes are analyzed, these techniques are referred as to Multi-criteria Decision Making (MCDM), or Multi-criteria Decision Analysis (MCDA). This is a vast research area. A recent review of the state-of-the-art of MCDA techniques was compiled by Figueria et al. [76]. Also, the application of MCDM to energy planning problems is studied by Hobbs and Meier [77]. Similarly, Loken [78] and Pohekar and Ramachandran [79] have reviewed the use of MCDM for energy planning.

There are some examples of application of MCDA and MCDM techniques to multi-objective DER planning. Tang and Tang [80] propose a weighted-sum for the optimization of DG location and size. It analyses four distinctive objectives. Although the DG modeling is still simplistic (a snapshot analysis), the authors addressed the problem of how to chose appropriate weights, depending on the planner preferences. They propose to use the Analytical Hierarchy Process (AHP) for this purpose, a recognized decision-making method [77]. Zangeneh and Jadid [81] in contrast, focus on how to obtain diverse solutions of the Pareto front using a single-objective minimization. They propose to use the Normal Boundary Intersection method to generate evenly distributed solutions in the Pareto set. They consider three objective functions, the total cost of DG (installation and operation), the cost of energy losses and the cost of energy not served. The modeling of the DG planning problem is still very simplified. Moreover, it is not clear from the case study proposed if this approach would be more effective than specialized MOEA (such as SPEA2 or NSGA-II) in finding a well spread, diverse and accurate Pareto front.

Barin et al. [82] explore the problem of choosing the best planning option from a "previous list of viable places for installation". Hence, they focus on the *a posteriori* multi-criteria decision-making problem, assuming that the multi-objective optimization problem has already been solved. They propose to use the Bellman–Zadeh algorithm. Following this algorithm, each objective of every solution is normalized to obtain a *normalized membership* value between 0 and 1 (0 been the worst performance, and 1 being the best performance). Weights are assigned to each membership value, according to its importance. Then, solutions are ranked according to the highest value of its worst normalized membership. This can be understood as a mini–max approach, in which the maximum distance to the goal (i.e. the worse performance in a weighted and normalized objective) is minimized. An interesting aspect is that the method facilitates the use of qualitative criteria for DG planning, such as security, physical space and vandalism. Qualitative criteria, such as social acceptability, are commonly hard to quantify numerically, but important to consider in some DG developments.

5. Discussion and conclusions

5.1. Discussion

From the review in Section 4, some trends can be identified in terms of the optimization methods utilized and the detail of the DER model. It can be observed that "classical" approaches, such as weighted-sum or the ε-constrained method are being gradually replaced by state-of-the-art MOEA, particularly second-generation SPEA2 and NSGA-II (Fig. 5). Classical approaches remain a useful option when detailed preference information is known *a priori*, and when the objective of the planning exercise is to find a single solution that represents a single point-of-view. The use of multi-attribute analysis has been proposed when the exogenous nature of DER investments is recognized. Multi-attribute analysis is not an optimization method, though it can be used to evaluate multiple impacts of unplanned (or random) DER developments.

The key characteristic of second-generation MOEA is the use of elitism [36], as already mentioned. Elitist MOEA have been

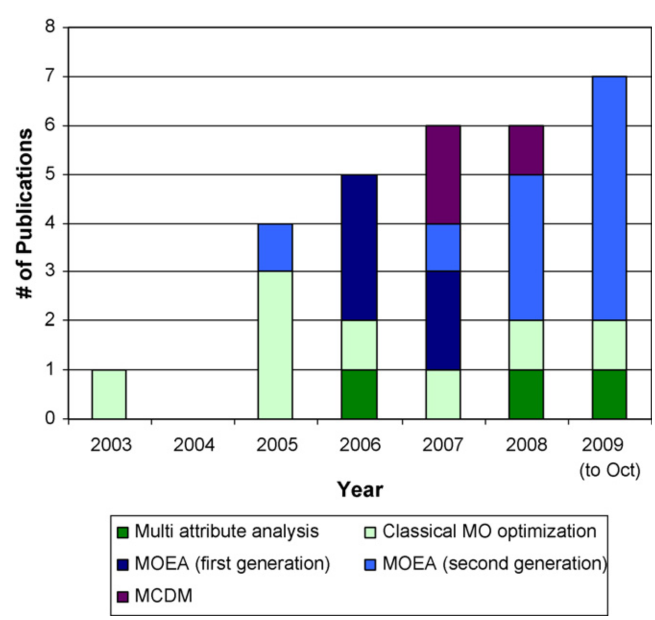

Fig. 5. Number of multi-objective DER planning publications per type of method used and per year.

demonstrated to out-perform non-elitist MOEA, hence, it is expected that in the coming years specialized MOEA of the second generation will be used widely in this area, while the use of first-generation MOEA should diminish. The concept of "constraint-dominance" permits the handling of constraints within the multi-objective formulation. Although initially proposed to be used with NSGA-II, this concept can be applied to any MOEA. At present it is used only by a small number of authors, though, it is expected that "constraint-dominance" will be more widely adopted in coming years.

MOEA permit the identification of a large number of Pareto front solutions, and provide information on the trade-offs and correlations between planning objectives. Moreover, EA permit the evaluation of complex models of DER. As a result, it is possible to observe that the detail of the DER models has evolved together with the use of MOEA. For example, most publications reviewed propose methods to evaluate the stochastic behavior of DER and load, either by means of probabilistic load flow, MCS, or stochastic simulation. Probabilistic load flow provides a fast evaluation of the stochastic behavior of the power system, though it limits the evaluation of controllable DER, and requires simplifying assumptions of the PDF of some DER, as already discussed. In contrast, the use of MCS and stochastic simulation permits a more accurate representation of some DER, such as wind generation, and can evaluate controllable DER. Though, a major drawback of the MOEA-MCS framework is the long computational evaluation time required. Hence, a key avenue for research is the parallel-computing implementation of MOEA-MCS DER planning approaches, and the use of clustering techniques to reduce the number of power flow evaluations.

Some authors still base the analysis of one unique DER solution on a single snapshot analysis of the power system. It must be emphasized that snapshot analyses are not appropriate to model most DER, which are variable in nature. Hence, these approaches are limited and only applicable to very specific DER types and circumstances (e.g. back-up DG units, capacity assessment of networks). As the use of renewable energy resources (most of which are variable in nature), heat-led CHP and Demand Side Management (DSM) become more widespread, simplistic models for DER planning will not be sufficient to generate useful knowledge.

Few techniques consider the controllability of DER. The few approaches that do illustrate that the use of MOEA permits the incorporation of "inner optimization" algorithms in the objective evaluation. The inner optimization algorithms, formulated commonly as an Optimal Power Flow algorithm, facilitate the simulation of controllable energy storage, controllable loads and controllable DER units. It is expected that the possibility of inner optimization algorithms will be exploited more widely, as the concept of active management of DER, Demand Side Management (DSM), and smart networks becomes widespread.

The papers reviewed highlight the benefits of a multi-objective formulation, and a wide range of technical and economical objectives are formulated. This demonstrates the flexibility provided by the multi-objective approach. Most of the authors recognize that one of the drivers for DER development is the environmental benefit(s) that can be obtained from an adequate integration of these technologies. As a result, new approaches incorporate explicitly environmental objectives. Moreover, the variety of case studies proposed highlight that multi-objective DER planning can be used to study different incentives schemes, analyze different impacts from a single stakeholder perspective or to determine compromise solutions that benefit different stakeholders. However, evidence of real applications in support of decision-making has still to be published.

5.2. Conclusions

In a future where a larger share of energy will be supplied from distributed sources, and where potentially a larger number of stakeholders will be involved, multi-objective planning tools will be needed to provide compromise solutions, and guide the optimal development of the system. Hence, multi-objective DER planning is a novel area that has gathered increased interest in recent years. This paper has presented a critical review of the state-of-the-art of multi-objective DER planning methods. Key aspects of the techniques that need to be considered in implementation have been highlighted and recent trends in the area have been discussed.

Some future avenues for the research in multi-objective DER planning can be identified. For example, multi-objective DER planning methods have yet to be applied to analyze the wide implementation of controllable loads and DSM. DSM and load controllability will gain prominence in a future where the impacts of energy use will be more carefully scrutinized and managed. Moreover, the use of electric vehicles (EVs) has been proposed as one solution to reduce carbon emissions from transport. EVs can be utilized as a sizeable and distributed form of electrical energy storage. The analysis of the impacts of EVs in the power system can be formulated within the multi-objective framework, where different perspectives of the problem can be represented.

In all cases, an adequate level of detail must be provided in the optimization models of active DER and active networks, in order to provide realistic solutions. Moreover, the focus must lie not only in the supply of electricity; as the interaction of electricity networks, gas networks, heat networks and DER will be essential in a future with a more decentralized and decarbonized energy supply. In addition, this research area will benefit greatly from publications that study real case studies in which the support to multifaceted decision-making scenarios is demonstrated.

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